Urban Rail Corridor Control Through Machine Learning: An Intelligent Vehicle-Highway System Approach

SNEHAMAY KHASNABIS, TOMASZ ARCISZEWSKI, SYED KHURSHIDUL HODA, AND WOJCIECH ZIARKO

Traffic control along an urban rail corridor with closely spaced stations can be considered a sequence of decision-making stages. A train on an urban rail corridor that connects two terminal points with a number of intermediate stations can follow various regimes of moving and stopping, which identify individual driving scenarios. The execution of these regimes may result in different values of attributes that describe driving scenarios, namely, travel time, energy consumption, passenger comfort, and others. An attempt is made to demonstrate how to develop decision rules for driving scenarios along an urban rail corridor that can optimize travel time, energy consumption, and passenger comfort, using the concept of machine learning. Machine learning is a science that deals with the development and implementation of computational models of learning processes. The concept of knowledge acquisition through inductive learning as an intelligent vehicle-highway system approach is explored to establish some initial decision rules. A computer model, REGIME, was developed for the estimation of values of evaluation criteria, such as travel time, energy consumption, and passenger comfort levels for a hypothetical rail corridor for various driving scenarios. Next, a commercial learning system, ROUGH, was used in conjunction with the examples created through REGIME to develop decision rules. The learning algorithm is based on the theory of rough sets. The feasibility of machine learning in automated knowledge acquisition to develop decision rules for complex engineering problems, such as urban rail corridor control, is demonstrated. Further research is needed to verify the rules developed before these can be applied.

Machine learning so far has had only limited applications to knowledge acquisition in civil engineering (*1*). However, there are some examples of the application of machine learning in the areas of conceptual design (*2,3*). A feasibility study of automated acquisition of knowledge of traffic control along an urban rail corridor was conducted at Wayne State University as a part of a program on intelligent vehicle-highway systems (IVHS). In this paper, the authors explore the concept of machine learning to develop decision rules for optimum control along an urban rail corridor. An earlier version of this paper was published previously (*4*).

PROBLEM STATEMENT

A train on an urban rail corridor connecting two terminal points with a number of intermediate stations can follow various regimes of moving and stopping, which identify individual driving scenarios. The execution of these regimes may result in different values of attributes that describe these scenarios, namely, travel time, energy consumption, passenger comfort, and others.

The concept of preprogrammed driving for urban rail corridors, as proposed in the literature will permit an automated selection of driving scenarios consistent with the distribution of ridership demand along the corridor (*5*). The driving scenarios are likely to change with the time of day as the demand changes. This concept is consistent with IVHS technology that aims at the integration of the vehicle, the facility, and the driver using the state-of-the-art communication, computer, and electronic technology (*6*).

When a large number of train driving scenarios is considered, the evaluation of individual scenarios and selection of the optimal one becomes difficult because of the complexities involved in analyzing these scenarios. An alternative approach is a knowledge-based selection. In this case, the optimal scenario may be selected using a knowledge-based decision support tool. This paper examines such an approach.

OBJECTIVES

The paper is based on a pilot study to explore the concept of knowledge acquisition through inductive learning to establish decision rules for an urban rail corridor. Ideally, one would like to

- Minimize travel time,
- Minimize energy consumption,
- Maximize access, and
- Minimize level of discomfort.

In actuality, it is not possible to minimize travel time and energy consumption at the same time because these two are nearly inversely related entities, as evidenced from empirical studies (*5*). The question of maximizing access has never been satisfactorily resolved in the literature. Passenger discomfort levels are associated with acceleration and deceleration characteristics of the train, and these are difficult entities to quantify. The objective of this paper is to demonstrate how to develop decision rules for driving scenarios along an urban rail corridor that can improve travel time, energy consumption, and comfort levels of passengers.

RAIL TRAFFIC CONTROL

Traffic control along an urban rail corridor with closely spaced stations can be considered a sequence of decision-making stages. In

S. Khasnabis, Department of Civil Engineering, Wayne State University, Detroit, Mich. 48202. T. Arciszewski, Systems Engineering Department, School of Information Technology and Engineering, George Mason University, Fairfax, Va. 22030. S.K. Hoda, H. Carl Walker Engineers, 445 W. Michigan Avenue, Suite 101, Kalamazoo, Mich. 49007. W. Ziarko, Department of Computer Science, University of Regina, Regina, Saskatchewan, Canada.

this study, three evaluation criteria are used: travel time that is based on regimes of motion, energy consumption, and comfort levels.

Regimes of Motion

Typically, the train operator has the option of selecting regimes of motion for individual segments (Figure 1) from four basic regimes, A through D, as discussed (*5*):

- *Regime A:* The interstation spacing is shorter than the critical spacing; critical spacing is the minimum distance between stations needed for the train to attain its maximum speed (Figure 1a).
- *Regime B:* The interstation spacing is longer than the critical spacing. The train maintains a sustained level of maximum speed before deceleration is initiated for the next stop (Figure 1b).
- *Regime C:* The interstation spacing is longer than the critical spacing. However, as an energy conservation measure, the train starts coasting (decelerating at a very slow rate) immediately on reaching its maximum speed and continues to coast until deceleration is initiated as the train approaches the next station (Figure 1c).
- *Regime D:* Regime D represents an intermediate condition between Regimes B and C that allows the train to travel at its maximum speed and to coast between two stops. The train accelerates to its highest speed, travels at the maximum speed for a predetermined period (as described in Regime B), and starts coasting (as described in Regime C) before the deceleration process is started. Within Regime D, infinite combinations are possible, depending on the instant when coasting is initiated. If coasting begins immediately before deceleration, the resulting is Regime B as a limiting condition. If, on the other hand, coasting is initiated immediately upon the attainment of maximum speed, Regime C will result as the other limit (Figure 1d).

Energy Consumption

Studies of Hamburg rail systems by empirical and computer simulation techniques have demonstrated the importance of different driving regimes in the context of energy consumption (*7*). The trade-off between energy consumption and travel time, developed from time-speed-energy consumption data, was used in this study to develop surrogate measures of energy consumption for varying travel times in the form of an empirical relationship (Figure 2). Although this relationship does not explicitly consider different regimes of motion, lower energy consumption resulting from longer coasting and consequent longer travel times are incorporated in this relationship (*8*).

Four models were developed for estimating energy consumption for the purpose of this study using the data presented in Figure 2. These models included simple, polynomial, logarithmic, and exponential models. The following exponential model was used for the study reported here.

$$Y = 1322.5 * 10^{(-1.0097e-2X} \ldots (A) \qquad R^2 = 0.983$$

where

X = travel time surrogate and
Y = energy consumption surrogate.

Passenger Comfort Levels

Every change in the acceleration/deceleration phase is associated with a level of discomfort for the passenger. The rate of acceleration/deceleration (second derivative of speed with respect to time) is commonly termed "jerk." It was assumed that the level

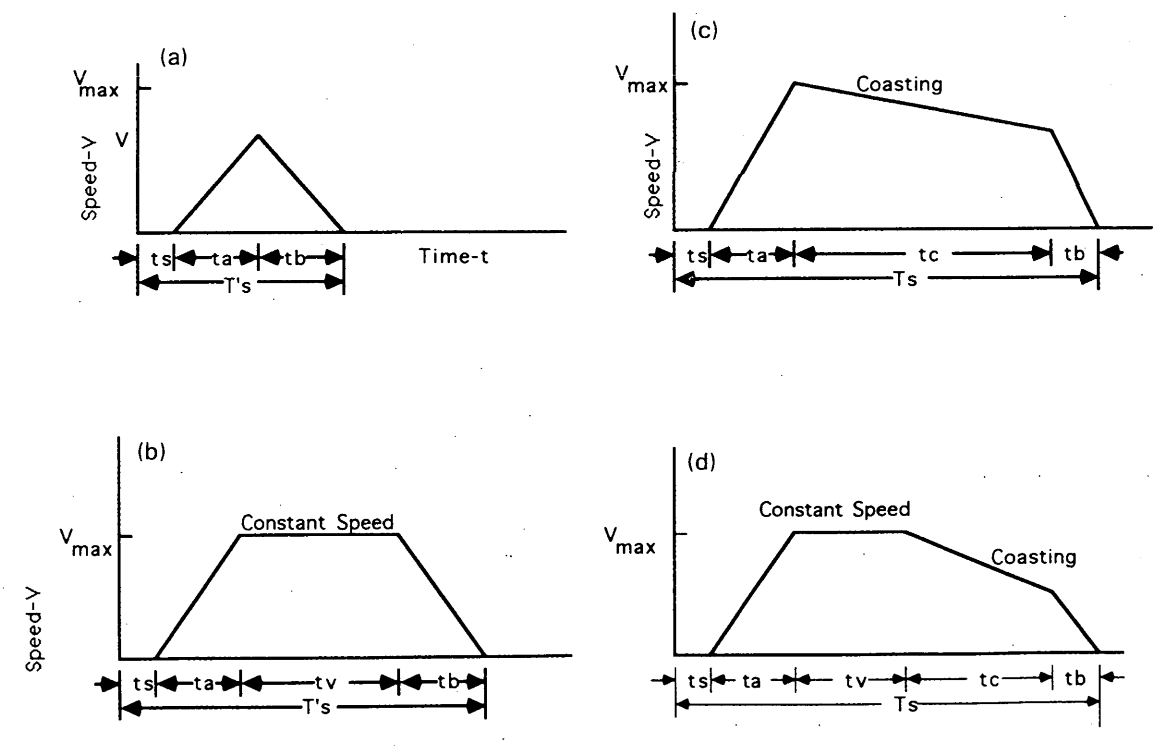

FIGURE 1 Interstation travel regimes (*5*). (*a*) Regime A, (*b*) Regime B, (*c*) Regime C, and (*d*) Regime D.

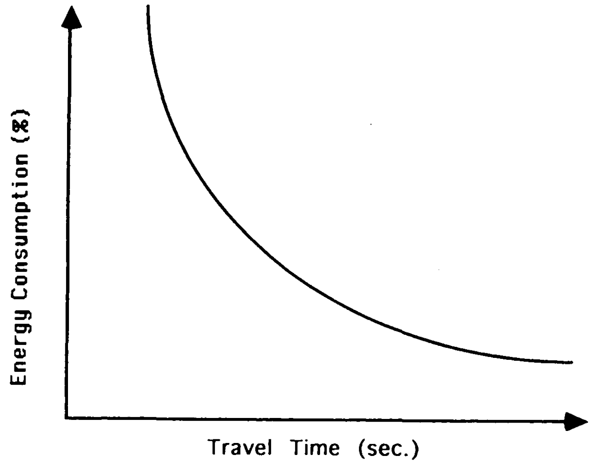

FIGURE 2 Travel time verses energy consumption trade-off (5).

of discomfort experienced by a passenger is measured by the number of jerks during a given pass of the train along the entire corridor. Ideally, not only the frequency of jerks but also their respective magnitudes should be considered. However, magnitude was considered too complex to quantify for the purpose of this study.

A review of acceleration/deceleration characteristics indicates that for a typical interstation travel, a total of two instances of jerks will be experienced during the acceleration phase, two during the deceleration phase, and one during the beginning of the coasting operation. Further, for every skip-stop operation, a total of four instances of jerk can be "saved," resulting from the elimination of deceleration and acceleration operation as the train approaches and leaves the station in question, respectively.

METHODOLOGY

The primary objective of this study was to apply a learning system as an automated knowledge acquisition tool for an urban rail corridor. The following methodology was used.

Machine Learning

Machine learning is the process of generating decision rules representing logical relationships between various combinations of attributes and their values. It is a science that deals with studies and development and implementation of computational models of learning and discovery processes. Learning systems are computer programs that transform input in the form of data (usually examples) into knowledge (usually in the form of decision rules).

A decision rule is a logical relationship between a group of attributes called "independent attributes" and a single attribute called a "dependent attribute." In this case, independent attributes are those that are controlled by the rail traffic operator, whereas dependent attributes can be only indirectly controlled. Therefore, independent attributes affect the values of dependent attributes. For example, an independent attribute "skipping one or two stops" affects the value of the dependent attribute "travel time."

ROUGH as a Machine Learning Tool

Automated knowledge acquisition was conducted using ROUGH, Version 1.1, a commercial inductive learning system developed by Ziarko (*9*). This algorithm utilizes the theory of rough sets proposed by Pawlak (*10*). Its objective is to produce decision rules for the classification of examples into one of the categories of the dependent attribute.

In the theory of rough sets, the determination of decision rules is based on the analysis of individual attributes in the context of a given collection of examples. This analysis includes the determination of the dependency relationship between the dependent attribute and any group of independent attributes, identification of a minimal set of independent attributes that are necessary and sufficient to produce decision rules, and the determination of the relative importance of individual attributes from this group.

ROUGH conducts the learning process in two stages. First, it performs the analysis of dependency factors for individual attributes and identifies a set of "reducts" for a given collection of examples. The term reduct signifies a minimum and sufficient collection of attributes describing a given system. This stage can be considered an analysis and modification of the representation space for given examples. In the second stage, actual learning occurs, and the system uses individual reduct attributes to produce decision rules using these attributes.

Study Approach

A computer program, REGIME, was developed for the estimation of values of evaluation criteria, which included travel time and surrogates of energy consumption and comfort level for a given train driving scenario along an assumed corridor. The necessary algorithms for computing travel times were obtained from Vuchic (*5*). Equation A, derived by the authors of this paper from Hamburg rail data, was used for estimating energy surrogates. The number of jerks experienced during a complete journey for each scenario was computed from first principles.

Although the computation of travel time for Regimes B and C is relatively straightforward, for Regime D it is somewhat complex, because of an infinite number of possibilities when coasting may be initiated. The model provides the user with a range of possible values of the coasting speed for different skip-stop combinations to help the user converge to a definite solution. The model produces the output at the individual station level (microscopic) as well as the corridor level (macroscopic).

All the driving scenarios were then identified by the condition attributes in binary form by assigning yes or no values (Table 1). After identifying the scenarios, the decision attributes, that is, total travel time, energy consumption factor, and passenger comfort, were determined. The decision attributes were identified by high, medium, and low desirability. The condition attributes and decision attributes were then entered in the ROUGH system as inputs to develop decision rules.

Study Area

Evaluation of individual scenarios was produced for a hypothetical urban rail corridor of 50 station spaces (sections) divided into five segments. The two end segments, Segments 1 and 5, consist of four

TABLE 1 Binary Representations of Condition Attributes

Segment	Condition Attributes	Binary Decision	
No. 1 and 5	Constant Speed	Yes	No
	Coasting	Yes	No
	Constant speed and Coasting	Yes	No
	One stop skipped	Yes	No
	Two stops skipped	Yes	No
No. 2 and 4	Constant speed	Yes	No
	Coasting	Yes	No
	Constant speed and Coasting	Yes	No
	One stop skipped	Yes	No
	Two stops skipped	Yes	No
No.3	Constant speed	Yes	No
	Coasting	Yes	No
	Constant speed and Coasting	Yes	No
	One stop skipped	Yes	No
	Two stops skipped	Yes	No

station spaces. Segments 2 and 4 are the two intermediate segments, each consisting of 12 station spaces. The central segment, 3, contains 18 station spaces. Each spacing was assumed to be 2,000 ft for a total corridor length of 100,000 ft. The rail corridor analyzed is thus a symmetrical one, with Segments 1 and 2 being mirror images of Segments 5 and 4, respectively, and Segment 3 being the central portion.

It was assumed that the decisions taken for Segments 1 and 5 would be identical. Similarly, it was assumed that Segments 2 and 4 are described by identical decisions. Therefore, the entire rail corridor is described when decisions for three different segments are known (for Segments 1 through 3). For each of these segments, five binary decisions about train operations are to be made. Thus, the entire problem of train control is represented as a sequence of 15 decision-making stages. At these stages, decision making requires answering binary (yes/no) questions (Table 1).

When all these questions are answered for the three different segments identified, a train-driving scenario is produced in the form of a sequence of 15 answers. In this model, the total number of train-driving scenarios is large, although it is significantly smaller than 2^{15} because some combinations of answers are infeasible.

RESULTS

The results are presented in two sections. First, the output of the software REGIME is presented in both microscopic (station) and macroscopic (corridor) levels. Next, the results of using the macro level output as an input to ROUGH to develop decision rules are presented. Finally, a brief discussion of the rationale of some of the decision rules thus developed is provided.

REGIME Output

The basic input for REGIME is maximum speed, demand, headway, acceleration, deceleration, coasting deceleration, interstation distance, and the total length of the corridor. The input values for the study are shown as follows:

Input	*Value*
Maximum speed	60 mph
Demand	45,000 passengers per hour
Headway	2.00 min
Acceleration	5 ft/sec^2
Deceleration	6 ft/sec^2
Coasting deceleration	1 ft/sec^2
Station waiting time	35 sec
Interstation distance	2,000 ft
Total distance	100,000 ft

Table 2 shows the micro level output of REGIME. Table 2 indicates that when Regime B is used, operating speed improves from 27.08 ft/sec obtained for no-skip operation to 41.41, 50.29, and 56.32 ft/sec for one-stop-skip, two-stop-skip, and three-stop-skip operations, respectively. At Regime C, skipping more than one stop results in a dysfunctional operation as the gradual drop in speed results in 0 speed. This is a consequence of coasting over an extended distance, caused by skipping more than one stop. The speed level attained at Regime D is between corresponding speeds at Regimes B and C for respective skip-stop operations.

Table 3 shows the macro level output of REGIME. The following is an interpretation of the first row in Table 3, a scenario in which the

TABLE 2 Output of REGIME Model (Micro Level)

		Skip Stop Scenario			
Regime	**Operating Data**	**0 Stop**	**1 Stop**	**2 Stops**	**3 Stops**
B	Operating Speed (ft/s)	27.08	41.41	50.29	56.32
	Travel Time (sec)	73.86	96.59	119.32	142.04
C	Operating Speed (ft/s)	26.96	37.11	0.00	0.00
	Travel Time (sec)	74.19	107.78	0.00	0.00
	Coasting Speed (ft/s)	79.70	39.39	0.00	0.00
D	Operating Speed (ft/s)	26.97	41.34	50.26	56.31
	Travel Time (sec)	74.16	96.76	119.39	142.06
	Coasting Speed(ft/s)	80.00	82.00	84.00	86.00

TABLE 3 Output of REGIME Model (Macro Level)

Scenario	No. of Jerks	Travel Time (seconds)	Energy Consumption Factor
B1-B2-B2	72	2056.76	129.33
B0-B1-B2	104	2465.83	81.45
D0-D2-D2	110	2298.79	98.37
C0-D2-D2	110	2298.98	98.35
C0-D1-B2	124	2550.49	74.01
C0-B2-D1	117	2478.84	80.26
D0-B2-B2	96	2263.72	102.35
D1-B2-C1	97	2338.22	94.09
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train would travel in: (*a*) Regime B, skipping one stop in Segments 1 and 5; (*b*) Regime B and skipping two stops in Segments 2 and 4; and (*c*) Regime B and skipping two stops in Segment 3 will result in 72 jerks, 2,056.76 sec of travel time, and 129.33 surrogate units of energy consumption for the entire corridor consisting of 100,000 ft.

ROUGH Output

REGIME was used to analyze 102 train driving scenarios, and for each scenario, estimates of the values of three evaluation criteria were produced. Next, these cases were used to prepare examples for inductive learning. The preparation of examples required the transformation of the evaluation criteria from interval into nominal attributes high, medium, and low. For instance, it was assumed that short travel time, low energy consumption, and high comfort (small number of jerks) all have high desirability, whereas long travel time, high energy consumption, and low comfort (large number of jerks) all have low desirability.

Automated knowledge acquisition was conducted using ROUGH to learn about driving scenarios for an urban rail corridor. Scenarios were defined by 15 condition attributes (Table 4). Three decision attributes or logical extensions of the three measures of effectiveness are as follows:

1. D1, Desirability for passenger comfort,
2. D2, Desirability for travel time, and
3. D3, Desirability for energy consumption.

Four machine-learning processes were performed using the ROUGH system. In the first process, comfort was considered as a decision attribute, and a total of 46 decision rules were developed (Table 5). Next, travel time was considered as a decision attribute, and a total of 41 decision rules were developed (Table 6). In the third process, energy consumption factor was considered as a decision attribute, resulting in a total of 52 decision rules (Table 7). In the fourth and final learning process, all decision attributes were considered together. A total of 71 decision rules were obtained (Table 8).

It is beyond the scope of this paper to offer exact interpretation of the above rules and, more importantly, to review the rationale behind these rules. Just to provide an example on how to interpret these rules, referring to Table 8, rule 69, the following explanation is offered.

To achieve high desirability in comfort (small number of jerks), medium desirability in travel time (medium travel time), and high desirability in energy consumption (low consumption levels) a driving scenario encompassing the following conditions should be fulfilled:

1. Coasting in Segments 1 and 5;
2. No constant speed and coasting in Segments 1 and 5;
3. Skipping one stop in Segments 1 and 5;
4. Skipping one stop in Segments 2 and 4;
5. Skipping one stop in Segment 3; and
6. No skipping two stops in Segment 3.

A review of these rules indicates that Condition 2 is automatically preempted by Condition 1 and thus is redundant. The essence of the remaining conditions is that the combination of coasting and skipping one stop in each segment will result in high desirability in comfort levels and in energy consumption levels. Further, skipping more than one stop may result in inordinately long travel times (particularly if Regime B is involved). As such, skipping more than one stop is discouraged. These rules thus appear logical and reasonable.

CONCLUSIONS

The objective of this paper is to explore the concept of knowledge acquisition through inductive learning to establish decision rules for an urban rail corridor. The study demonstrates the feasibility of using machine learning in automated knowledge acquisition about complex engineering problems such as urban rail traffic control.

TABLE 4 Description of Condition Attributes

Condition Attributes	Notation
Constant Speed in the 1st and 5th Segments	S11
Coasting in the 1st and 5th segments	S12
Constant speed and Coasting in the 1st and 5th segments	S13
Skipping One stop in the 1st and 5th segments	S14
Skipping Two stops in the 1st and 5th segments	S15
Constant speed in the 2nd and 4th segments	S21
Coasting in the 2nd and 4th segments	S22
Constant Speed and Coasting in the 2nd and 4th segments	S23
Skipping One stop in the 2nd and 4th segments	S24
Skipping Two stops in the 2nd and 4th segments	S25
Constant speed in the 3rd segment	S31
Coasting in the 3rd segment	S32
Constant speed and Coasting in the 3rd segment	S33
Skipping One stop in the 3rd segment	S34
Skipping Two stops in the 3rd segment	S35

TABLE 5 Rules by Decision Attribute D1 (Passenger Comfort) as Output of ROUGH

Rule	Condition Attribute															Decision Attribute
No.	S11	S12	S13	S14	S15	S21	S22	S23	S24	S25	S31	S32	S33	S34	S35	D1
1		N		N			N		N	N		N		N	N	L
2		N		N			N	N	N	N		N		Y	N	M
3		N		N			N	Y	N	N		N		Y	N	L
4		N		N			N		N	N		N			Y	M
5		N		N			N		N	Y		N		N		M
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43		Y		Y					N	N				Y	N	M
44		Y		Y					Y	N				Y	N	H
45		Y		Y						Y				Y	N	H
46		Y		Y											Y	H

TABLE 6 Rules by Decision Attribute D2 (Travel Times) as Output of ROUGH

Rule	Condition Attribute															Decision Attribute
No.	S11	S12	S13	S14	S15	S21	S22	S23	S24	S25	S31	S32	S33	S34	S35	D2
1		N		N			N		N	N		N			N	L
2		N		N			N		N	N		N			Y	M
3		N		N			N		N	Y		N		N	N	M
4		N		N			N		N	Y		N		N	Y	H
5		N		N			N		N	Y		N		Y		H
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38		Y		Y					N	N				Y	N	L
39		Y		Y					Y	N				Y	N	M
40		Y		Y						Y				Y	N	H
41		Y		Y											Y	H

TABLE 7 Rules by Decision Attribute D3 (Energy Consumption) as Output of ROUGH

Rule	Condition Attribute															Decision Attribute
No.	S11	S12	S13	S14	S15	S21	S22	S23	S24	S25	S31	S32	S33	S34	S35	D3
1		N	N	N					N	N		N				H
2		N	N	N				N	N	Y		N				L
3		N	N	N				Y	N	Y		N		N		H
4		N	N	N				Y	N	Y		N		Y		M
5		N	N	N					Y			N	N			M
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49		Y	N	Y				Y				N	Y	Y	N	M
50		Y	N	Y				Y				Y		Y	N	M
51		Y	N	Y				Y							Y	L
52		Y	Y													L

TABLE 8 Rules by Decision Attributes D1, D2, and D3 as Output of ROUGH

Rule No.	Condition Attribute															Decision Attributes		
	S11	S12	S13	S14	S15	S21	S22	S23	S24	S25	S31	S32	S33	S34	S35	D1	D2	D3
1		N	N	N			N	N	N	N				N	N	L	L	H
2		N	N	N			N	N	N	N				N	Y	M	M	H
3		N	N	N			N	N	N	N				Y		M	L	H
4		N	N	N			N	N	Y	N				N		H	H	M
5		N	N	N			N	N	Y	N			N	Y		H	M	M
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68		Y	N	Y					N	Y		Y		Y	N	H	H	M
69		Y	N	Y					Y					Y	N	H	M	H
70		Y	N	Y											Y	H	H	L
71		Y	Y													H	H	L

The rules developed are based on three separate evaluation criteria: passenger comfort, travel time, and energy consumption. Additionally, a set of rules was developed with all of the three attributes combined. No effort was made in this study to explain these rules, to validate them, or to assess how they can be applied in actual train control. The large number of decision rules and their interaction reflects the complexity of the rail corridor control. To gain further insights into this problem, an automated rule verification method is recommended on the basis of the performance of the learning system, measured by various empirical error rates.

Machine learning in rail traffic control is a new complex and interdisciplinary research, and more work is needed to determine the feasibility of machine learning in rail corridor control, to develop better understanding of the problem, and to prepare a program that would lead from research to practical application of results. The technique of machine learning appears to complement the emerging IVHS area.

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